

Simulating the Core Dynamics of a Social Dilemma. Individual Choices, Time and Sanctions in the Tragedy of the Commons

Nicola LETTIERI ^{a,b 1}, Margherita VESTOSO ^b

^aISFOL, Rome, Italy

^bUniversity of Sannio, Dept. of Law, Economics, Management, Quantitative Methods, Benevento, Italy

Abstract. The understanding of the way in which collective phenomena emerge from the interaction between individual behaviors, environment and institutions, can play a crucial role in supporting the design of more contextualized policies. An apparently effective policy can easily fail if policy makers do not consider the interplay between individual decision making and social aggregate dynamics. This paper presents an ongoing research exploiting an agent-based simulation model to explore the core dynamics of the Tragedy of the Commons (ToC), a social dilemma known for being behind a series of societal problems spanning from pollution to resource depletion and climate change. The goal is twofold: capture the basic processes through which the ToC emerges and evolves; explore in an artificial society the effects of different strategies aiming to contrast the phenomenon. Our attention is focused on the interplay between different factors proven to be involved in the genesis of this dilemma: the selfish rationality of human beings, the temporal dimension of individual choices and the potential impact of sanctions.

Keywords. policy modeling, computational social science, Tragedy of the commons, agent-based models, evolutionary simulations, intertemporal choice

Introduction

The understanding of the way in which collective phenomena emerge from the interaction between individual behaviors, environment and institutions, can play a crucial role in supporting the design of more effective policies. A relevant limit of public policies is that they often fail in evaluating the effects that a given strategy could produce on the society. Part of this difficulty is due to fundamental features of social complexity: social systems are characterized by multiple ontological levels with multiple connections, proceeding not only from the micro to the macroscopic levels but also back from the macro to the micro levels [11], [26].

Recently, the complexity science perspective has fostered innovative approaches to policy making aiming at importing exact science methods and tools, advanced computing techniques and complexity mathematics into socio-economic policy (e.g. [2], [16]) and into rule making [36]. Interesting works have been published in this field [9]

¹ Corresponding author: Nicola Lettieri, ISFOL, C.so d'Italia 33, 00198, Rome, Italy; E-mail: n.lettieri@isfol.it.

showing how the intersection of complexity sciences with public policy and management is leading to new insights into very perplexing policy issues allowing the design of more successful policies “conceived not as something that takes place off-line, outside systems, but as a constitutive process interacting with self-organized system behavior” [50].

A fundamental contribution can be given, in this scenario, by computer simulations models as they provide new insights into social dynamics that can inform the design of effective policy solutions. Policy models are often unable to grasp and forecast complex social processes including the reaction of individuals to policy decisions, the aggregate effect of their interactions, and their consequences on large spatial-temporal scales [39], [50]. As frequently highlighted in recent policy informatics literature [14], [32], [33], simulation models can be in various way helpful in addressing this issue: they can not only offer new ways to predict how social systems co-evolve with the policy, but also a deeper understanding of the mechanics underlying the issues policy makers want to address. More in general, they promote a scientific habit of mind in policy making, pushing towards the adoption of explicit objectives expressed in quantitative and verifiable way, enabling testable predictions about the impact of the choices and of the actions undertaken. By revealing tradeoffs, uncertainties, and sensitivities, simulations can discipline the public dialogue about options making judgments more considered. Finally computer simulation models offer a chance to overcome the drawbacks of a disciplinary approach to policy design. Individual and collective phenomena that affect policy effectiveness are investigated by a number of distinct disciplines from sociology to psychology, law, or economics and simulations help us in understanding how the phenomena studied by these disciplines work together and influence each other.

According to the vision so far described, this paper presents an ongoing research exploiting an evolutionary agent-based simulation model to explore the core dynamics of the Tragedy of the commons (hereinafter ToC), the social dilemma theorized as being behind a series of societal problems spanning from pollution to resource depletion and climate change. The research goal is twofold: identify the core dynamics through which the ToC emerges and evolves and explore the effects of different strategies aiming to contrast the phenomenon. Our attention is focused, in particular, on the interplay between different factors proven to be involved in the genesis of this dilemma: the selfish rationality of human beings, the temporal dimension of individual choices and the potential impact of sanctions.

The paper is structured as follows: in Section 1 we present the ToC focusing attention on two of the most discussed factors involved in generating this social dilemma. Section 2 offers a general overview of the agent-based model we are developing and testing. Section 3 sketches preliminary results of the experiments so far conducted. Section 4 draws some conclusions and discusses future developments.

1. A puzzling dilemma for policy makers: the Tragedy of the Commons

The complexity of public policies is often connected with the need to cope with social dilemmas, situations that “*arise whenever a group of individuals must decide how to share a common resource while balancing short-term self-interests against long-term group interests*” [22]. In general terms, social dilemmas are characterized by two fundamental features: a) each individual of the community taken into account receives

a higher payoff for a socially defecting choice (e.g. using all the available energy, polluting neighbors) than for a socially cooperative choice, no matter what the other individuals in society do, but b) all individuals are better off if all cooperate than if all defect.

Social dilemmas are extremely relevant because they often create or lead to social issues, problems, or even disasters. Given the ubiquity and the global importance of some of them, it is essential for policy maker to learn how to deal with them: since social dilemmas become more complex there is an increasing need to understand how to design effective policies. That's why the scientific interest in social dilemmas - particularly those resulting from overpopulation, resource depletion, and pollution - has grown dramatically in the last ten years. The attention is shifting from pure laboratory research towards interdisciplinary approaches characterized by the cooperation between different research areas (spanning from computer science to anthropology, from biology, economics, neuroscience, to political science and psychology) aiming to develop together a unifying theoretical framework.

The ToC is a well-known social dilemma described for the first time by Garret Hardin in 1968 [23] and deriving by the fact that individuals acting autonomously and rationally according to their self-interest behave contrary to the interest of the whole group depleting common resources. Over the time, ToC has been considered as the prototype of a range of dilemmatic situations that occur in different social contexts from micro (local) to macro (global) level. The considerations made about the Tragedy can be therefore extended virtually to any instance in which society appeals to an individual exploiting a common resource to restrain himself for the general good by means of his conscience. ToC is often mentioned in connection with different issues from economic growth to environmental protection. It has been used in analyzing behavior in the fields of economics, evolutionary psychology, game theory, politics and sociology (extremely known the analysis conducted by Elinor Ostrom [40], [41]).

The evolution of the ToC has been traced back to many different social and individual causes. It is possible anyway to identify two basic factors involved in triggering the ToC, the two factors we focused on in designing of our simulation model.

a) Selfish rationality

In his paper, Hardin identifies in the individual tendency to increase well-being, the core mechanism generating the Tragedy. *"As a rational being"*, he states, *"each herdsman seeks to maximize his gain. Explicitly or implicitly, more or less consciously, he asks, 'What is the utility to me of adding one more animal to my herd?' This utility has one negative and one positive component. 1) The positive component is a function of the increment of one animal. Since the herdsman receives all the proceeds from the sale of the additional animal, the positive utility is nearly +1. 2) The negative component is a function of the additional overgrazing created by one more animal. Since, however, the effects of overgrazing are shared by all the herdsmen, the negative utility for any particular decision-making herdsman is only a fraction of -1."* In this context, adding together the component partial utilities, a rational individual concludes that the best choice for him is to continue to add animals to his herd. But, as this is the conclusion reached by each rational herdsman sharing a commons, the tragedy becomes unavoidable.

b) Intertemporal choices and temporal discount

The selfish rationality is not the only ingredient of the ToC. As highlighted in psychological literature [12], the Tragedy is strictly connected, like many social dilemmas, with the "time lag": the fact that behaviors resulting in immediate reward

leads to long-term negative effects (see Platt's concept of "social traps" [43]). A recent study [30] focusing on climate change shows that a crucial role is played, in the genesis of the ToC, by the way in which human beings deal with time while making what are called "intertemporal choices". Intertemporal choices concern options that can be obtained at different points in time (e.g. buying expensive cars today or saving the money to ensure a sizable pension in the future) and that often oppose a smaller but sooner prize (e.g., a modest amount of food ready at hand) against a larger but delayed outcome (e.g., a more distant but also richer foraging opportunity). The research, published in 2013, aims to test how groups of individuals respond to the challenge of avoiding dangerous climate change in a setting that rewards defection immediately and rewards cooperation over three different time horizons to represent intra- and intergenerational discounting. According to the results of the public-good experiments presented in the paper, the difficulty of avoiding dangerous climate change (but the analysis can be extended to many other social dilemmas with the same structure and also to other instances of the Tragedy) arises not only from the tension between group and self-interest generated by rational selfish behaviors, but is also exacerbated by climate change's intergenerational nature. The dilemma lies in that *"present generation bears the costs of cooperation, whereas future generations accrue the benefits if present cooperation succeeds, or suffer if present cooperation fails"*.

The interplay between the two above mentioned factors makes it difficult to counteract the evolution of the Tragedy and suggests the introduction of incentives to cooperate, such as mutual coercion [23], punishment [17], [29] rewards [30] or even reputation [38] and shame [29]. A crucial issue for policy makers is therefore the comprehension of the way in which incentives can be administered in order to effectively fight the spread of the social dilemma.

2. An evolutionary model of the Tragedy of the Commons

As above highlighted, the research here presented aims to explore the core dynamics underlying the ToC and, at the same time, to investigate the way in which these dynamics can be altered by means of well tailored incentives to cooperate. To this end, drawing inspiration from a series of interesting research works on this topic [7], [13], [27], [31], [53]), we have implemented a simulation model using *NetLogo* [48], an open source multi-agent agent-based programming language and integrated modeling environment widely used for simulation purposes in the social sciences. The model is available online at <https://www.openabm.org/user/1294/models>.

2.1. Theoretical framework

Taking cue from the considerations sketched in Section 1 about *selfish rationality* and *time discount*, we tried to build a comprehensive, multi-theoretical model in which facts are stylized according to different existing theories of human behavior. Without going into details, we can say that our choices in designing the model are mainly grounded in two theoretical frameworks:

- *Rational choice theory*: developed by the economist Gary Becker in 1976 [3] and still widely used to model human decision making in economics, sociology, and political science, rational choice theory revolves around the idea that people make

decisions about how they should act by comparing the costs and benefits of different courses of action.

- *Intertemporal choice*: the scientific investigation of the intertemporal choices (as said above, the decisions with consequences that play out over time) has produced interesting findings in different research areas. After an initial emphasis on finding what mathematical model (typically a delay discounting function) would better fit the empirical data [34], [51], current research is focusing on exploring the cognitive mechanisms that produce the observed behavioral patterns, and tracing their evolutionary roots [4].

Drawing upon insights offered by both rational choice theory and intertemporal choice research, we decided to explore the impact that the mechanism of sanction/punishment can have in preventing the evolution of the ToC. As widely acknowledged in a huge and heterogeneous literature, sanctions are essential in promoting social cooperation [17], [19] even in dilemmatic situations like the ToC [30]. A still challenging research goal, however, is to experimentally determine how different kinds of sanction can dynamically affect the evolution of social dilemmas taking into account the interplay between factors like selfish rationality and intertemporal choices and computer simulations have proven to be a suitable tool in this regard (see, for example, [35]).

Our model is extremely simplified with respect to the phenomena under investigation while, as authoritatively claimed [10], policy modeling will more and more often need complex simulations to yield conclusions concretely applicable to real world problems. Even very abstract models, anyway, can be useful when they are able to grasp the core mechanics of the socio-economic dynamics impacted by policy measures. In this perspective, the simulation here presented is expected to help to figure out what can be done to increase cooperation in dilemmatic situations (how, to what extent and when apply sanctions) offering insights that can integrate more traditional regulatory impact assessment tools [52]. Policy solutions inspired by simulation experiments can account for both individual decision making and the counterintuitive effects generated by the interactions between the individuals, the environment and the policy measures. Obviously, when needed, it will be possible to increase the level of realism of the model developing scenarios more grounded in real data in which the actors, their behaviors and the environment are described with a higher level of detail. This will offer policy makers results with a higher predictive power and, therefore, more immediately exploitable in real settings.

2.2. Modeling approach

Every simulation is based on a more or less abstract model that simplify the representation of a target phenomenon. The design of the model and the way in which facts are stylized inside the model, depends on the research objectives, the scientific approach and the researcher's point of view about the causes of the phenomenon under investigation.

Different approaches to the simulation of social phenomena have emerged so far from system dynamics [18], [44], to microsimulations [49] and agent-based simulations [11], [15], [20]. In particular, the agent-based paradigm (ABM) is a specific kind of social simulation that can be defined as a “*computational method that enables a researcher to create, analyze, and experiment with models composed of agents that*

interact within an environment”[20]. Based on the identification of the scientific explanation with the reproduction “*in silico*” (i.e. in a computer simulation) of the social processes being investigated, ABM has contributed to promote a generative [15] approach to social science research: social macro dynamics and structures are interpreted, described, reproduced and explained as the result of micro-interactions between computational entities (agents) simulating the behavior of real individuals. In this perspective, modeling the structural properties of social systems and exploring their spatio-temporal development via computer simulation are crucial steps to provide explanations of complex social outcomes.

Over time, ABM research has generated different approaches to modeling phenomena that are very close to those discussed in this paper such as the effects of punishment on cooperation. These approaches, roughly speaking, can be classified into two macro-categories. On the one hand, there are simulation models whose main objective is the analysis of the socio-cognitive underpinnings of human behaviors. This category of models, in which agents are endowed with complex cognitive architectures reproducing mental processes - *Beliefs, Desires, Intentions* (BDI) [45] and *Beliefs, Desires, Obligations, Intentions* (BOID) [6]. On the other hand, there are *evolutionary models* which are somehow bio-inspired and are not so much interested in the internal dynamics of the agent but focus on the effects of mutual influences between individuals and the social environment and on analyzing the condition under which pre-programmed strategies can become stable patterns of behavior. So far, evolutionary simulation models have been frequently used to understand how social outcomes spanning from cooperation [1], [21], [25], to social learning [37], can be explained as the result of adaptation strategies. The study of punishment, in particular, has already exploited evolutionary models [5], [24].

From a technical point of view, the core of the evolutionary approach is represented by modeling and programming techniques trying to mimic natural processes of adaptation. One of the most relevant of these techniques is the genetic algorithm (GA) that imitates the evolutionary process of learning based on research and exploration [28]. Often used in social simulation research [8], [41], GA allows to model populations of adaptive agents that are not fully rational in the sense that they are only capable of refining the strategies adopted by trials and errors. Using the selective reproduction of agents and the constant addition of random mutations, most effective strategies can emerge thanks to the research conducted by a succession of generations of agents. According to this second approach, we used GA to simulate learning, where learning occurs across generations of agents rather than during an agent’s life. Obviously, we interpret our GA not in biological but in cultural terms [46].

2.3. Model overview

Model’s structure has been designed aiming to stylize and reproduce somehow the basic interaction structure leading to the ToC. 100 agents move in an environment which is a grid of $41 \times 41 = 1681$ patches that contains a given number of randomly distributed tokens. When an agent reaches a token, the agent takes possession of the token but another token appears in another position of the environment so that the total number of tokens remains always the same. All agents are equally able to reach the tokens but the speed with which the agents move to reach the tokens varies from agent to agent and this speed is encoded in the agents’ genes. The simulation is a succession of generations each composed of 100 agents.

The agents of the first generation have random genes and this means that each agent moves at a different speed. The 10 agents that happen to have better genes and therefore run faster and reach more tokens (fitness) generate 10 offspring each and the offspring inherit the genes of their (single) parent with the addition of some random variations (genetic mutations) that can make some offspring to have better genes and to run faster than their parent. The $10 \times 10 = 100$ offspring are the second generation of agents and the simulation goes on for 5 generations. While moving in the environment to reach the tokens, agents pollute the environment and the quantity of pollution depends on the speed with which they move. An agent which moves faster pollutes the environment more than an agent which moves more slowly. Pollution reduces the agents' fitness. The fitness of an agent and, therefore, the probability that the agent will have offspring depends not only on the number of tokens that the agent is able to reach, but also on the level of pollution of the environment. Living in a polluted environment implies a reduction of fitness which is proportional to the level of pollution.

In this way we have stylized the basic dynamic of the ToC, leading the agents to face with the dilemmatic issue: either they move more slowly and eat fewer tokens and in this way they do not contribute to the pollution of the environment, or they move faster and eat more tokens but they pollute the environment. The problem is that all the agents contribute to the pollution of the environment. If an agent because of its genes "decides" to move more slowly in order not to pollute the environment, this does not mean that the environment will not be polluted because other agents may "decide" to move faster and, therefore, the environment will equally be polluted. An agent has only disadvantages if it moves slowly and, therefore, to have more fitness all agents will move fast and the environment will become progressively more polluted - with an increasing damage for all the agents.

3. Experiments and preliminary results

Starting from the basic interaction structure so far sketched and drawing upon the theoretical framework above outlined to model agents' behavior, we are conducting a series of experiments manipulating different relevant variables of the simulation model. We have introduced in the model the possibility to apply a "sanction" to agents that move too fast and pollute the environment producing therefore a higher level of pollution. The sanction produces a reduction of the fitness of the agent that exceeds a given speed limit and its amount can be varied according to researcher's aim. Our main goal is to explore interplay between selfish rationality, punishment and intertemporal choice on the emergence and development of cooperative behavior exploiting the genetic algorithm as a device to simulate learning processes.

The parameters of the simulation are numerous (token density, agents' life length, speed limit etc.). Each of them can affect the result of the experiment and each of them has a specific semantic value. Currently, we are investigating how the combination of different kinds of sanction with different temporal scenarios affects the evolution of ToC dynamics. The simulation model allows different sanction "regimes":

- *fixed*: the sanction has the same fixed value for each agent that exceeds the limit;
- *speed proportional*: the sanction value is given by difference between real speed of the agent and speed limit;
- *fitness proportional*: the sanction has a value which is proportional (10%) to the fitness of the agent that exceed the speed limit.

The sanction regimes can be combined with different temporal scenarios in which the effects of pollution and the effects of sanctions are more or less delayed in time. Results so far obtained (Table 1) are showing interesting correlations between the delay of sanction and cooperative behavior: the effectiveness of sanction depends not only on the amount and type of sanction, but also on the time of its application. In particular, we found that a large delayed sanction reduce the effectiveness of the sanction itself, so the agents keep on exceeding the speed limit. Moreover, we also noted that when the sanction is proportional to the agents’ fitness it seems to be anyway effective, even if it is largely delayed.

Table 1. Simulation results. The speed limit is set on the same value (2 in a range 1 to 5) during all the experiments. “+” indicates that the sanction is “effective”, (the sanction allows to contain the speed of the whole population) under the speed limit; while “x” indicates an “ineffective” sanction.

		Sanction delay		
		None	Medium (10 ticks)	High (30 ticks)
Sanction regime	Fixed (low: -1 fitness)	x	x	x
	Fixed (medium: -2.5 fitness)	+	+	x
	Fixed (high: -5 fitness)	+	+	+
	Speed proportional	+	x	x
	Fitness proportional	+	+	+

4. Conclusions

Even if very preliminary, results so far obtained allow us to draw some conclusions about future experiments and the developments of the model. As to the first point, we are planning to conduct other experiments sweeping parameters over a range of scenarios to identify uncertainties and important thresholds. Our attention will be focused, in particular, on the interplay between the delay of pollution effects, the sanctions and the temporal dimension of individual choices. More in general, the analysis of the experiments have highlighted the need of a more semantically rich solutions to stylize the way individuals deal with the interaction structure that characterizes the ToC. The hyperbolic discount function so far adopted does not account for cognitive dynamics that play a significant role in determining the evolution of intertemporal choice.

In real settings, the individual propensity to cooperate with other individuals is conditioned by factors that go beyond the simple (even if temporally discounted) assessment of the costs and the benefits deriving from selfish behavior and sanctions. The choice to cooperate in dilemmatic scenarios (in our case by refraining from polluting or depleting common resources) is also conditioned by the prescriptive power of social norms and, therefore, by all the mechanisms that supports their spreading and stabilization. That’s why, taking also cue from a recent simulation work on the cognitive implications of the ToC [53] we are planning to endow agents with a cognitive architecture (a software model of reasoning used for programming intelligent agents) accounting for the process of norm internalization.

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